Brain– machine interfaces

Chapter 49

Brain–machine interfaces

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A *brain–machine interface* (BMI) is a biohybrid system primarily intended to act as an alternative communication channel for people suffering from severe motor impairments, such as those with a motor neuron disease or with spinal cord injuries. A BMI can be realized either invasively, using electrodes implanted in the cortex or placed directly on its surface (an electrocorticogram) or by using non-invasive imaging systems. In either case, the aim is to measure the cortical or neurophysiological correlates of brain activity during voluntary cognitive tasks. The focus of this chapter is on non-invasive BMI (seeVassanelli, Chapter 50, this volume for a discussion of invasive interfaces) where the technologies available include: *electroencephalography* (EEG) which measures changes in brain electrical activity through the skull; *magnetoencephalography* (MEG) which measures changes in the magnetic fields produced by brain activity using highly sensitive magnetometers; and various techniques, detailed below, that detect changes in the brain's hemodynamic response (blood flow) and that are indicative of activity in localized brain areas.

Among these non-invasive approaches EEG-based BMI is the most widely investigated. Event-related de-synchronization/synchronization (ERD/ERS) of sensorimotor rhythms (SMRs), the P300 event-related potential (a wave of electrical activity linked to decision making), and steady-state visual evoked potential (SSVEP) are the three main cortical activation patterns in EEG used for designing an EEG-based BMI. Being a pattern recognition system, a BMI involves multiple stages: brain data acquisition, pre-processing, feature extraction, and feature classification along with a device to communicate or control with or without explicit neurofeedback.

Despite worldwide extensive research towards making the BMI as practical as possible for daily use, there are still several challenges to be overcome. One crucial challenge is to account for non-stationary brainwaves dynamics resulting in time-variant performance. Also, some people may find it difficult to establish a reliable BMI with sufficient accuracy, although most improve over time with repeated practice. Despite these challenges, the BMI research is progressing in two broad application areas: alternative communication by replacing neuromuscular pathways, and neurorehabilitation by helping to activate desired cortical areas for targeted brain plasticity.

Biological principles of non-invasive interfaces

A brain–machine interface (BMI), also called a brain–computer interface (BCI), is normally established by uniquely identifying repeatable metabolic or electric brain activity (e.g. cortical activation) patterns occurring in response to a set of well-defined cognitive tasks. The activation patterns are detected using a pattern recognition system (based on one of the technologies listed above), whose output can be used to select keypad letters, display messages, play computer games, control household devices, control prosthetic/orthotic limbs, or command and control a tele-presence robotic device or a smart wheelchair. Thus, via the cognitive task, the BMI enables communication with a computer-controlled machine or device directly through brain activation, bypassing the peripheral nervous and muscular systems. BMI is primarily aimed at providing alternative communication to people suffering from severe motor impairments such as motor neuron disease (MND) and spinal cord injuries (SCIs).

EEG-based approaches

In addition to speech, gestures, including facial expressions and motor tasks such as right hand movement and/or left hand movement, are naturally used by human beings in their routine communications. Coincidently, it was found that hand movement execution may result in changes in EEG signals known as sensorimotor rhythm (SMR) activations in the form of event-related desynchronization (ERD) in the contra-lateral hemisphere (relative to the moved hand) and event-related synchronization (ERS) in the ipsilateral hemisphere (Pfurtscheller and Neuper 2001). The ERD is manifested as a reduction in EEG signal amplitude mainly in the rolandic alpha (or μ band) and the ERS as an enhancement in the signal amplitude mainly in the β band. Fortunately, it has been found that the planning or preparation for real hand movement and hand movement imagination also lead to very similar cortical activations in the sensorimotor cortex (Pfurtscheller and Neuper 2001), therefore those with movement impairments can instead perform motor imageries to generate similar cortical activations in μ and β bands (cf. Figure 49.1). Pioneered by Pfurtscheller's group in Graz (Pfurtscheller et al. 2000), the sensorimotor rhythm (SMR) modulation in the form of ERD/ERS is by far the most predominant neurophysiological phenomenon used in devising a non-invasive EEG-based BMI.

Uniquely identifiable cortical activations also occur in another EEG-based measure—event-related potentials (ERPs). Two of the most commonly used in devising EEG-based BMIs are P300 and steady-state visual evoked potential (SSVEP). In P300-based BMI, all the objects or options that may need to be selected are arranged in the form of a grid as part of a graphical user interface (GUI). Exploiting the odd ball paradigm concept, the objects are displayed repeatedly one-by-one in a sequential order and the BMI user focuses his/her attention on the desired object. This creates a uniquely identifiable event-related potential change after a latency of about 300 ms. Farwell and Donchin (1988) were the first to use P300 as the basis for a BMI.

In SSVEP-based BMI, corresponding to each of the objects or options to be selected, a flickering display is created either through an external device such as an LED or a flickering graphical display as part of a GUI. Each of the displays flickers at a certain fixed frequency. When a BMI user focuses his/her attention on one of the displays, the cortical activations (i.e. the amplitude of the potential) corresponding to the flickering frequency and its harmonics in the occipital cortex get enhanced (Wolpa and Wolpa 2012, chapter 14).

MEG-based BMI

Another non-invasive approach to recording electrical brain activity is by means of recording the magnetic field produced by the electrical impulses generated by cortical neurons, through a process called magnetoencephalography (MEG). An MEG system may contain up to three hundred sensors and must be operated at the temperature of liquid helium. The MEG provides whole-head views, a high spatiotemporal resolution and its signal's spatial distribution is impervious to the varying masses within the structure of the head. Mellinger et al. (2007) showed that a sensorimotor rhythm (SMR)-based BMI using MEG was as effective as that using EEG.

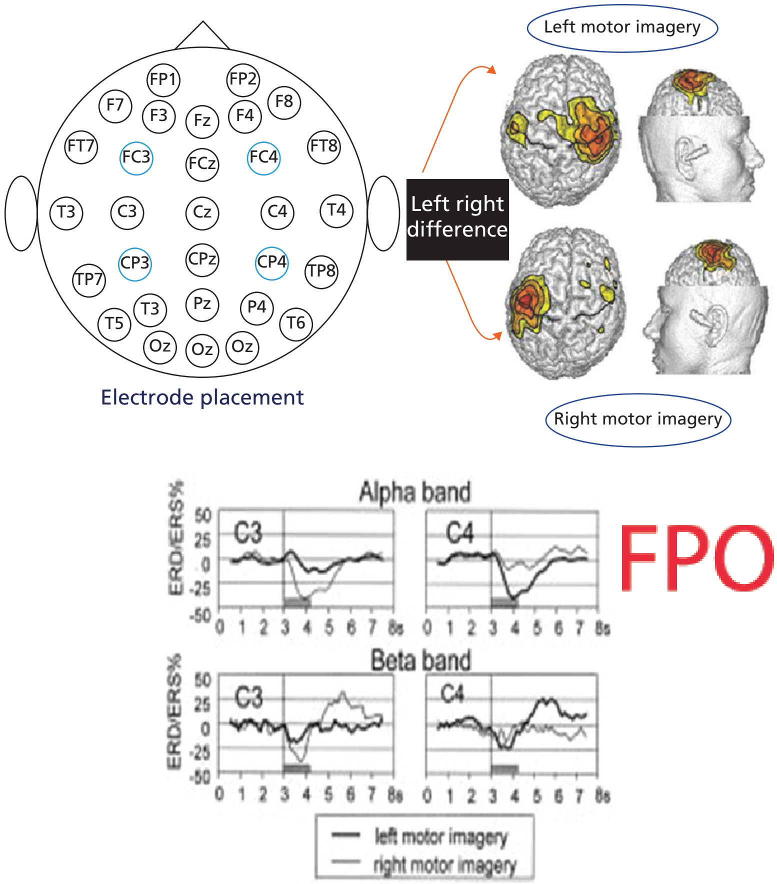

Figure 49.1 ERD/ERS Phenomena in EEG-based SMR BMI. *Left panel*: EEG channels C3 and C4 connections in bi-polar mode are highlighted in blue. ~~*Middle*~~ *panel:* ERD maps for a single subject calculated for the cortical surface of a realistic head model. The spline surface Laplacian method was applied to the bandpass filtered (9–13 Hz) single-trial EEG data and the distribution of the alpha band ERD was calculated for left and right motor imagery. ~~*Right*~~ *panel:* Grand average ERD curves recorded during motor imagery from the left (C3) and right sensorimotor cortex (C4). The ERD time courses were calculated for the selected bands in the alpha range for 16 subjects. Positive and negative deflections, with respect to baseline, represent a band power increase (ERS) and decrease (ERD), respectively. The gray bars indicate the time period of cue presentation (modified from Pfurtscheller et al. (2000)).

BMI based on brain hemodynamics

In recent years BMI systems have also been devised based on the on-line detection of changes in metabolic brain activities in the form of the blood oxygen level dependent (BOLD) signals obtained from *functional magnetic resonance imaging* (fMRI). During mental tasks, neurons use up their energy supply, which must be replenished by the blood in the form of oxygen and glucose, and thereby allowing identification of areas of the brain that are active. Similar to MEG, fMRI offers a high spatial resolution but unlike MEG it is able to penetrate deep within the brain in order to measure neuronal activity. Yoo et al. (2004) demonstrated that volunteers were able to steer their way through a two-dimensional maze using an fMRI-based BMI by performing four different mental tasks each of which allowed separate areas of the brain to be activated. This study, although showing high accuracies, made use of only two participants and took around two minutes to generate each command which resulted in a relatively low information transfer rate.

BMI systems have also been developed based on the on-line detection of changes in metabolic brain activities in response to motor imageries tasks, in the form of hemodynamic signals obtained from near-infrared-spectroscopy (NIRS). The NIRS systems offer high spatial resolution but low temporal resolution. However, such quality systems may be too bulky and expensive for day-to-day constant use. The use of NIRS for BMI is a relatively new concept; it operates by measuring changes in both the regional cerebral blood flow (rCBF) and the cerebral oxygen metabolic rate ($rCMRO_2$). When certain areas of the brain become active they require more oxygenated blood and hence the detection of increased amounts of oxygenated hemoglobin signals. For this, the light of a certain wavelength is emitted then collected by a sensor which is subsequently analyzed. The attenuation which the light undergoes on its passage between emitter and sensor is an indication of the structure of the tissue which it has passed through. Coyle et al. (2007) were the first to study an NIRS-based SMR BMI which detected motor imagery tasks to make a binary choice. Although the system shows great potential, the study results in an information transfer rate (ITR) of 1 bit/min and does not contrast well when measured against other similar EEG-based systems. Its advantages lie in the fact that it is low-cost, convenient and portable for the user, and provides good temporal resolution when compared against MEG and fMRI.

The most recent entrant in the BMI field is a technique involving the detection of changes in cerebral blood flow velocity (CBFV), called Transcranial Doppler (TCD) sonography. By its design, TCD is inherently immune from electrical interference such as the power line interference which affects EEG recordings. TCD is a relatively cost-effective method of detecting changes in the brain when compared against MEG or fMRI and exhibits good temporal resolution and whose hardware is also relatively portable. It has been used for BMI in a mental task discrimination study (Myrden et al. 2011) involving nine able-bodied participants who were each asked to perform one of two mental exercises. Sensors placed at the left and right transtemporal windows detected a bilateral increase in the CBFV during a mental rotation task whilst a word generation task produced left lateralization.

Biohybrid systems

A biohybrid system implementing a BMI will be built around a pattern recognition system and thus, as seen in Figure 49.2, it requires a multi-stage system consisting of brain data acquisition, pre-processing, feature extraction, feature classification, and finally a command and control interface for controlling or communicating to a device, with or without an explicit neurofeedback. The most predominantly used brain signal is EEG, which is an ultra-low voltage signal with very low signal-to-noise-ratio (SNR), as the skull dampens signals, dispersing and blurring the electromagnetic waves created by the activations of cortical neurons. Therefore as part of the data-acquisition system, very high quality electrodes and a cap assembly are needed for appropriately attaching sensors to the scalp, following the international 10–20 system of electrode placement, and then high gain op-amp based amplifiers are normally used to substantially amplify the signal in appropriate frequency ranges, so as to obtain a practically useful signal.

Signal pre-processing

Raw EEG signals have a very low signal-to-noise (SNR) ratio due to several factors such as the interference from the electrical power line, motion artifacts, and EMG/EOG interference. Low

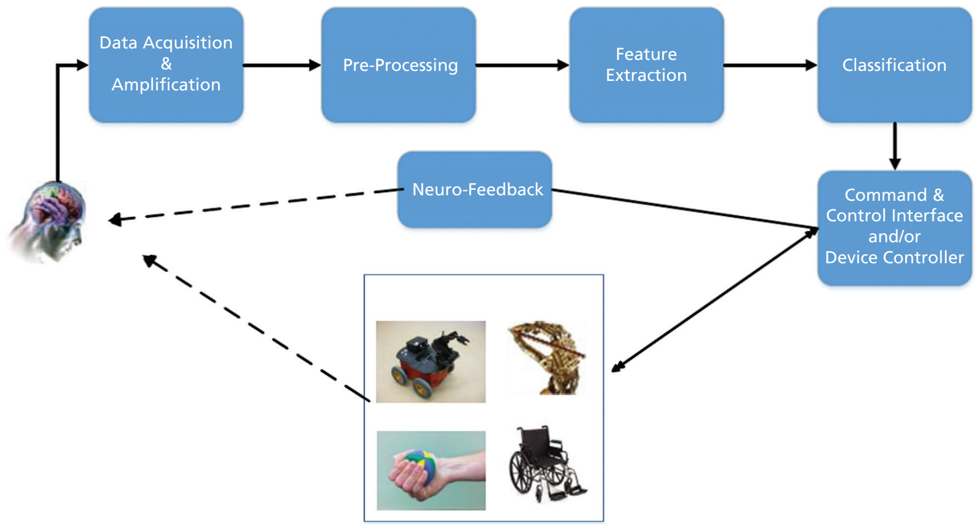

Figure 49.2 A Brain–Machine Interface.

SNR may also occur because EEG contributions from neuronal activations related with BMI tasks maybe overshadowed with the activations resulting from multifarious autonomic and other cognitive activities. Pre-processing is therefore carried out to remove unwanted components embedded within the EEG signal leading to increase in signal quality and resulting in better feature separability and classification performance. The pre-processing filter is designed in such a way that most of the EEG components unrelated with BMI tasks are suppressed. Pre-processing carried out using a recurrent quantum neural network (RQNN) based stochastic filter was reported by Gandhi et al. (2014a) to result in a statistically significant improvement in performance across multiple subjects.

Feature extraction

In the feature extraction stage, the pre-processed signal is used to extract features that are likely to provide uniquely identifiable patterns providing enhanced separability among the classes of cognitive tasks used to operate the BMI. The primary aim of feature extraction is to extract mental task-correlated information (or features) from the brain signal regardless of the quality of the EEG signal. The output of the feature extraction stage highly impacts on the performance of the following feature classification stage. For instance, the probability of correct brain state identification can be increased if the feature extraction stage transforms the EEG signal in such a way that the SNR is maximized as much as possible.

The main distinguishing features in all the EEG patterns used for BMI design are changes in power in certain frequency bands, e.g. ERD in SMR of the μ band. The power spectral density (PSD) is therefore the most commonly used feature for visually demonstrating the EEG modulations resulting from the BMI task-related cortical activations. Some form of PSD is also found to be one of the best features in enhancing BMI performance (Herman et al. 2008) and is the most widely used feature in BMI design. Other frequently reported features are band-power, wavelets, and common spatial patterns (CSP). A feature extraction technique using one of the higher order statistics methods called bispectrum, was shown to provide significantly enhanced performance (Shahid and Prasad 2011) by effectively accounting for the fact that the motor imagery (MI)-related EEG signals are highly non-Gaussian and have non-linear dynamic characteristics.

Feature classification

In the classification stage, a pattern classifier is designed for high accuracy in classifying the particular features obtained from the feature extraction stage. A range of linear and non-linear classification algorithms such as linear discriminant analysis (LDA), type-2 fuzzy logic, multi-layer perceptrons, and support vector machines, have been investigated and reported to provide mixed results (Herman et al. 2008). Some form of LDA is one of the most popular classification algorithms used in BMIs. One of the main reasons for the mixed performance of sophisticated classification algorithms is the non-stationary nature of the brain signals used in BMI design.

User interface, neurofeedback, and BMI operation

BMI systems often require a graphical command and control interface customized to their specific BMI paradigm to control user interaction and as well to issue commands to operate the intended device. In proportion to the detected cortical activations, some type of neurofeedback (often in a visual form) is created and provided to the BMI user in real-time to help assess his/her effectiveness in operating the BMI (cf. Gandhi et al. 2014b).

Normally a BMI operates in a cue-initiated timed paradigm, which is called a dependent or synchronous mode of operation. An SMR-based BMI can also be operated in a paradigm-free mode. This is called a self-paced or asynchronous mode of operation. Although the asynchronous mode is more natural to operate, it is difficult to achieve sufficiently reliable performance in this mode. However, a long-term constant use of a BMI is yet to be seen, though pilot trials of a range of BMI applications have been reported. Frequently reported applications include using BMI for environment control, typing letters, operating a robotic system or a wheelchair, and neurorehabilitation, e.g. by helping to activate desired cortical areas for targeted brain plasticity so as to restore movements in paralyzed limbs. A brief discussion of a range of promising applications reported recently follows.

Applications

The P300-based BMI has primarily been found to be well suited to tasks requiring direct selection. Commonly reported applications are spelling, smart home control, or internet browsing (Wolpa and Wolpa 2012, chapter 12). Several applications involving mobile robot or wheelchair control using control strategies involving SMR as well as P300 BMIs, either one type alone or a combination of both, have been reported. For safe wheelchair operation, it is essential that obstacle as well as collision avoidance is ensured at all cost. Robotic systems are therefore equipped with a set of appropriate range sensors along with an obstacle avoidance mechanism. As part of a shared control strategy, BMIs are primarily used either to initiate an autonomous navigation or to perform a step-by-step navigation control in a supervised mode, while the obstacle avoidance as well as collision avoidance is ensured by the robotic side controls. For instance, in Gandhi et al. (2014b), a shared control strategy involved a command and control interface, called an intelligent adaptive user interface (iAUI), wherein icons of basic movement commands such as forward, left, right, backward, and stop are displayed for selection by a two-class SMR BMI (cf. Figure 49.3). Through bi-directional communication, the positions of the movement commands in iAUI are re-organized based on the position of the mobile robot within the environment so that the most probable movement commands could be selected fastest using just a two-class BMI.

In recent years, a very promising application of the EEG/MEG-based BMI in post-stroke neurorehabilitation has been investigated by several research groups. In this the BMI is primarily used

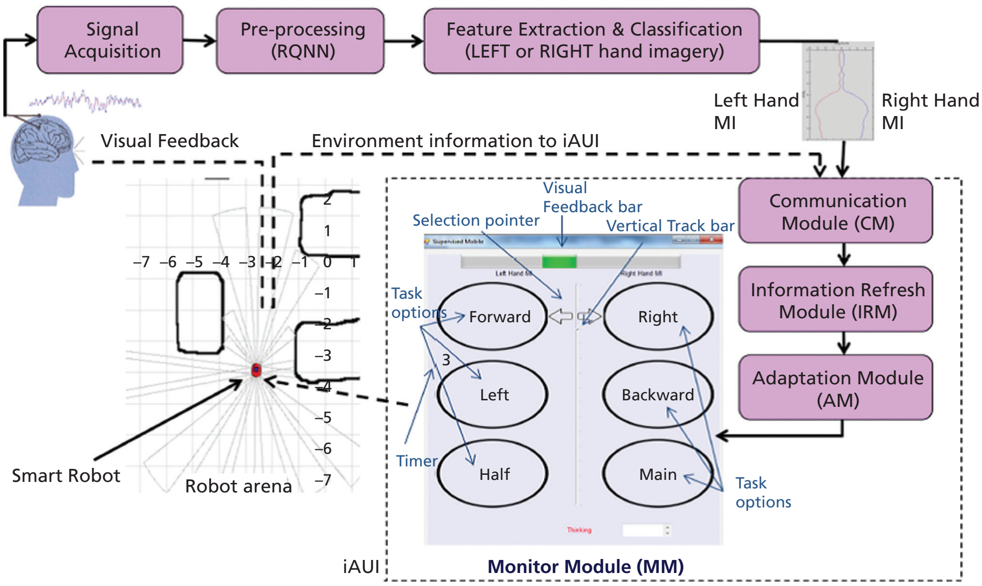

Figure 49.3 Intelligent adaptive user interface (iAUI) along with a complete BMI loop. (Adapted from Gandhi et al. (2014b).)

to detect cortical activations when the stroke sufferer is performing rehabilitation exercises. Based on the extent of cortical activations in the motor cortex, the BMI provides neurofeedback as well as commands a robotic exoskeleton if available, to perform physical movements. Thus the BMI helps facilitate focused physical practice as well as motor imagery practice of rehabilitation exercises (Prasad et al. 2010; Ramos-Murguialday et al. 2013), which is found to result in enhanced motor recovery even among chronic stroke sufferers (see Ballester, Chapter 59, this volume, for a discussion of neurorehabilitation paradigms).

Although there are no obvious technology risks with the use of non-invasive BMI, its effect over long-term usage is yet to be carried out. Some participants in pilot trials of SMR BMI have reported feeling tired and, in some cases, headaches after performing motor imageries to operate BMI for more than an hour or so. This is, however, very much dependent upon the kind of application, and type and quality of neurofeedback provided to the participants. Also, it is well known that people prone to epileptic seizures are adversely affected by the flickering displays used in ERP BMIs. In general cortical re-organization resulting from long-term use of BMIs is unlikely to have any adverse effect, as it is more like learning a new skill.

There are quite a few companies that have launched a range of BMI-related products[1] into the market. These companies primarily offer a hardware and software setup, which can be used to devise a prototype BMI very quickly for either some specific application or further research and innovation. As BMI systems are still mainly in the R&D stage, the companies offering products that provide, as much as possible, open access to data and system information (e.g. g.tec Austria) have much better market penetration, as these are preferred by university BMI labs around the globe.

[1] http://en.wikipedia.org/wiki/Brain%E2%80%93computer_interface

Future directions

There are still several challenges to be overcome before a BMI becomes practical to use on a daily basis. For acquiring a good quality EEG signal, active EEG electrodes requiring wet gel for attaching to the scalp are still the preferred option. These require professional support for applying to the user's head and the gel gets dried up over time, adversely affecting the quality of the skin contact. Urgent research is therefore needed towards devising good quality dry electrodes which can be easily attached to a head-gear that can be comfortably worn by the user without any professional support.

On the signal processing side, the main challenge is due to the inherently non-stationary characteristics of the brainwaves dynamics. The dynamics also change due to cortical plasticity resulting from repeated BMI usage over time. Also, it is not uncommon to find degraded electrode connections due to several engineering factors such as drying of the gel. As a result, the performance of the BMI classifier designed off-line using previously stored data deteriorates. In order to address this, there is a need to continuously monitor the EEG to ascertain whether there is a significant change or shift in its characteristics and thereby in the features extracted for devising the BMI (Raza et al. 2015). Once the change is detected, the BMI needs to be adapted to the new dynamics. If this adaptation can be automated through semi-supervised on-line training (Raza et al. 2016) so that it does not need constant professional support, it will go a long way towards making the BMI practical to use.

Another challenging issue has been that a substantial proportion of users find it difficult to operate a particular type of BMI, that is, their two-class BMI operating accuracy may be 70% or lower, and those people may be considered to suffer from a BMI aphasia. However, a person may not have aphasia for all types of BMIs at the same time; also, performance improves with training and experience. There is therefore now greater emphasis on developing multi-modal hybrid BMI (hBMI) by combining two different modalities wherein inputs are either received in parallel or sequentially. In the sequential arrangement, the first BMI acts as a brain switch. Also, an hBMI may combine two different EEG patterns, e.g. SSVEP and ERD/ERS in SMR. It can also be designed to combine one brain signal and a different type of input such as heart-rate (Shahid et al. 2011) or signals from an NIRS BMI or an eye-tracking system.

There has also been a lot of emphasis on mainstreaming the application of a BMI, so as to enhance its general acceptance in society, more like a consumer product. To this end, some promising works reported are BMI-driven computer games, BMI-based driver attention and fatigue monitoring, and BMI-enabled artistic expression such as music or painting (Wolpa and Wolpa 2012, chapter 23). However, the central focus of innovations in BMIs still remains targeted towards alternative communication for replacing impaired neuromuscular pathways and neurorehabilitation for helping to activate desired cortical areas for targeted brain plasticity.

Learning more

One of the most useful books worth consulting for more information is *Brain-Computer Interfaces: Principles and Practice* by Wolpa and Wolpa (2012). This book provides very comprehensive coverage of all aspects of both invasive and non-invasive BMIs. Although chapters are written by different authors, they are very well integrated and present a highly coherent description of the state of the art in BMI. The book is aimed at scientists, engineers, and clinicians at all levels having a basic undergraduate level background in biology, physics, and mathematics. An interesting BMI review paper by Silvoni et al. (2011), presents a thorough review of the progress of BMI in relation to post-stroke rehabilitation. Specifically, this paper contextualizes three popular approaches to BMI-based rehabilitation: substitutive strategy, classical conditioning strategy, and operant conditioning strategy.

There are also available several open-source and/or open-access software tools. One of the most widely used tools by BMI researchers is EEGlab[2]. It is a MATLAB-based toolbox for processing event-related EEG, MEG, and other electrophysiological data. It has a rich library of functions for blind source separation, time/frequency analysis, artifact rejection, event-related statistics, and visualization of averaged and single trial data. The other commonly used open source software library is that produced by the BioSig project[3]. The BioSig library is basically a toolbox for Octave and MATLAB with import/export filters, feature extraction algorithms, classification methods, and viewing functions. It can be very effectively used for processing a range of bio-signals such as EEG, ECoG, electrocardiogram (ECG), electrooculogram (EOG), electromyogram (EMG), respiration, and so on. A freely available BMI software system BCI2000[4] is another very useful tool for learning BMI technology as well as developing novel BMI applications. This is a general purpose system for BMI research and can be used for data acquisition, stimulus presentation, and brain monitoring applications. The BCI2000's vision is to become most widely used tool for diverse areas of real-time bio-signal processing and it is claimed that there are over 2700[5] users around the world.

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References

Coyle, S. M., **Ward, T. E.**, and **Markham, C. M.** (2007). Brain-computer interface using a simplified functional near-infrared spectroscopy system. *Journal of Neural Engineering*, **4**(3), 219–26.

Farwell, L. A., and **Donchin, E.** (1988). Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalogr. Clin. Neurophysiol.*, **70**(6), 510–23.

Gandhi, V., **Prasad, G.**, **Coyle, D.**, **Behera, L.**, **McGinnity, T. M.** (2014a). Quantum neural network-based ~~eeg~~ filtering for a brain–computer interface. *IEEE Transactions on Neural Networks and Learning Systems*, **25**(2), 278–88.

Gandhi, V., **Prasad, G.**, **McGinnity, T. M.**, **Coyle, D.**, and **Behera, L.** (2014b). EEG based mobile robot control through an adaptive brain-robot interface. *IEEE Transactions on Systems Man and Cybernetics: Systems*, **44**(9), 1278–85.

Herman, P., **Prasad, G.**, **McGinnity, T. M.**, and **Coyle, D. H.** (2008). Comparative analysis of spectral approaches to feature extraction for EEG-based motor imagery classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **16**(4), 317–326.

Mellinger, J., **Schalk, G.**, **Braun, C.**, **Preissl, H.**, **Rosenstiel, W.**, **Birbaumer, N.**, and **Kübler, A.** (2007). An MEG-based brain-computer interface (BCI). *NeuroImage*, **36**(3), 581–93.

Myrden, J. B., **Kushki, A.**, **Sejdić, E.**, **Guerguerian, A.**, and **Chau, T.** (2011). A brain-computer interface based on bilateral transcranial Doppler ultrasound. *PloS One*, **6**(9), e24170.

[2] http://sccn.ucsd.edu/eeglab/

[3] http://biosig.sourceforge.net/

[4] http://www.schalklab.org/research/bci2000

[5] http://www.schalklab.org/research/bci2000

Pfurtscheller, G., and **Neuper, C.** (2001). Motor imagery and direct brain–computer communication. *Proceedings of the IEEE*, **89**(7), 1123–34.

Pfurtscheller, G., **Neuper, C.**, **Guger, C.**, **Harkam, W.**, **Ramoser, H.**, **Schlögl, A.**, **Obermaier, B.**, and **Pregenzer, M.** (2000). Current trends in Graz brain–computer interface (bci) research. *IEEE Transactions on Rehabilitation Engineering*, **8**(2), 216–19.

Prasad, G., **Herman, P.**, **Coyle, D. H.**, **McDonough, S.**, and **Crosbie, J.** (2010). Applying a brain-computer interface to support motor imagery practice in people with stroke for upper limb recovery: a feasibility study. *Journal of Neuroengineering and Rehabilitation*, **7**(60), 1–17.

Ramos-Murguialday, A., **Broetz, D.**, **Rea, M.**, et al. (2013). Brain-machine-interface in chronic stroke rehabilitation: a controlled study. *Annals of Neurology*, **74**(1), 100–8.

Raza, H., **Cecotti, H.**, **Li, Y.**, and **Prasad, G.** (2016). Adaptive learning with covariate shift-detection for motor imagery-based brain–computer interface. *Soft Computing*, **20**(8), 3085–96.

Raza, H., **Prasad, G.**, and **Li, Y.** (2015). EWMA model based shift-detection methods for detecting covariate shifts in non-stationary environments. *Pattern Recognition*, **48**(3), 659–69.

Shahid, S., and **Prasad, G.** (2011). Bispectrum-based feature extraction technique for devising a practical brain-computer interface. *Journal of Neural Engineering*, **8**(2), 025014. doi: 10.1088/1741-2560/8/2/025014

Shahid, S., **Prasad, G.**, and **Sinha, R. K.** (2011). On fusion of heart and brain signals for hybrid BCI. *Proc. 5th Int. IEEE EMBS Conference on Neural Engineering*, Cancun, Mexico. IEEE, 5 pp.

Silvoni, S., **Ramos-Murguialday, A.**, **Cavinato, M.**, **Volpato, C.**, **Cisotto, G.**, **Turolla, A.**, **Piccione, F.**, and **Birbaumer, N.** (2011). Brain-computer interface in stroke: a review of progress. *Clinical EEG and Neuroscience*, **42**(4), 245–52.

Wolpa, J. R., and **Wolpa, E. W.** (2012). *Brain-Computer Interfaces: Principles and Practice*. New York: Oxford University Press.

Yoo, S., **Fairneny, T.**, **Chen, N.**, **Choo, S.**, **Panych, L.**, **Park, H.**, **Lee, S.**, and **Jolesz, F.** (2004). Brain-computer interface using fMRI: spatial navigation by thoughts. *Neuroreport*, **15**(10), 1591–5.